UDC 629.735.051-52(045)

T. A. Galaguz

INVESTIGATION OF INITIAL DATA INFLUENCE TO THE CONTROL LAW QUALITY

E-mails: T.A.Galaguz@yandex.ua

Abstract—*In the paper the influence of the initial data to the control law is investigated. Particularly the control quality under the different wind turbulence was analysed. Two flight control systems had been synthesized: with a Kalman filter, and with a Luenberger observer. Control laws robust optimization was performed.*

Index Terms—Unmanned aerial vehicle; flight control system; Kalman filter; Luenberger observer; the optimal regulator; Dryden filter

I. INTRODUCTION

Nowadays in the scientific research makes a special focus on unmanned air vehicle. One of the problems that solved is the control systems synthesis. Obtained control law must provide the necessary control quality. To solve this problem different approaches are used: a synthesis using the full and reduced order observer, fuzzy logic, and so on [2], [4], [5]. It should be borne in mind that the synthesis is performed for object with incomplete and inaccurate measurements of the state vector. Received control law should provide control quality in parametric disturbance influents.

Thus, accuracy of the object and disturbances mathematical model has a significant influence on the final result. Therefore, the investigation of initial data influence to the control law quality is advisable and actual.

II. DIGITAL CONTROL SYSTEM DESIGN WITH THE KALMAN OBSERVER

For the synthesis of robust control system with the Kalman filter it is necessary to define four state-space matrices of plant. It is also necessary to have characteristics of sensors noises and stochastic disturbances, which are acting on the plant [1], [2].

The condition of procedure of Kalman filter synthesis use is the white noises influencing the plant [1]. Turbulence of the atmosphere – is the colored noise. Therefore the peculiarity of the plant state space description is a necessity of forming filter (Dryden filter) including in its structure, which input is being disturbed by the white noise, and on an output we have the color noise which characterizes turbulence of atmosphere [6]. Thus the inputs of the extended plant in state-space will be disturbed by the white noise that is corresponds to the terms of the plant description for the synthesis of Kalman filter. And the color noise will act directly on our plant.

Such an object in state-space will be described with equation:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} + \omega_1; \qquad \mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u} + \omega_2,$$

where $\mathbf{A} \in R^{n\times n}, \mathbf{B} \in R^{n\times m}, \mathbf{C} \in R^{l\times n}, \mathbf{D} \in R^{l\times m}$, $1 < n$, m < n four aircraft state-space matrices; ω_1 - external disturbances vector; ω_2 - white noise of sensors with covariance matrix $\mathbf{V}_2$.

Description of stochastic disturbances (turbulent wind) can be obtained by passing the white noise through the proper forming filter. The model of forming filter is standardized in American practice [6].

Suppose the forming filter is represented in the state space by fore matrices

$$\left[\mathbf{A}_f \in R^{p\times p}, \mathbf{B}_f \in R^{p\times s}, \mathbf{C}_f \in R^{r\times p}, \mathbf{D}_f \in R^{r\times s}\right].$$

To adapt considered problem to the standard form, it is necessary to make use of separation theorem [69] possible. So the series connection of Dryden filter and an aircraft model performed. Result: state space model with vector $\mathbf{x}_{ex} = [\mathbf{x}_f, \mathbf{x}]'$ and four state space matrices

$$\left[\mathbf{A}_{ex} \in R^{(p+n)\times(p+n)},\ \mathbf{B}_{ex} \in R^{(p+n)\times(s+m)},\right.$$
$$\left.\mathbf{C}_{ex} \in R^{l\times(p+n)},\ \mathbf{D}_{ex} \in R^{l\times(s+m)}\right].$$

where

$$\left[\begin{array}{c|c} \mathbf{A}_{ex} & \mathbf{B}_{ex} \\ \hline \mathbf{C}_{ex} & \mathbf{D}_{ex} \end{array}\right] = \left[\begin{array}{cc|c} \mathbf{A}_f & \mathbf{0}_{p\times n} & \mathbf{B}_f \\ \mathbf{B}_g\mathbf{C}_f & \mathbf{A} & \mathbf{B}_g\mathbf{D}_f \\ \hline \mathbf{0}_{l\times p} & \mathbf{C} & \mathbf{D} \end{array}\right].$$

Matrix's input $\mathbf{B}_g$ is connected with input of the forming filter, which disturbs correspondent variables in state space of aircraft:

$$\mathbf{x}(i+1) = \mathbf{A}_d\mathbf{x}(i) + \mathbf{B}_d\mathbf{u}(i) + \eta;$$
$$\mathbf{y}(i) = \mathbf{C}_d\mathbf{x}(i) + \mathbf{D}_d\mathbf{u}(i) + \omega_2.$$

where η and ω_2 are white noises that are disturbing systems state as well as measurements.

For simplification index „ex" will not be used further.

As number of measurements l is less than number of phase coordinates n, it is necessary to define such an operator F (optimal filter):

$$\hat{\mathbf{x}} = F(\mathbf{y}, \mathbf{u}),$$

which minimizes error's norm $\varepsilon(i) = \mathbf{x}_{ex}(i) - \hat{\mathbf{x}}(i)$.

$\hat{\mathbf{x}}$ can be found by:

$$\hat{\mathbf{x}}(i+1) = \mathbf{A}_d\hat{\mathbf{x}}(i) + \mathbf{B}_d\mathbf{u}(i) + \mathbf{K}[\mathbf{y}(i) - \mathbf{C}_d\hat{\mathbf{x}}(i)], \quad (1)$$

where $\mathbf{K}$ the matrix of gain coefficients of optimal Kalman observer is determined by the expression

$$\mathbf{K} = \mathbf{Q}\mathbf{C}_d^{\ T}\left[\mathbf{V}_2(i) + \mathbf{C}_d\mathbf{Q}\mathbf{C}_d^{\ T}\right]^{-1}$$

And matrix of recovery error variance $\mathbf{Q}$

$$\mathbf{Q} = \mathbf{A}_d^{\ T}\mathbf{Q}\mathbf{A}_d - \mathbf{A}_d^{\ T}\mathbf{Q}\mathbf{B}_d\left(\mathbf{B}_d^{\ T}\mathbf{Q}\mathbf{B}_d + \mathbf{V}_2\right)\mathbf{B}_d^{\ T}\mathbf{Q}\mathbf{A}_d + \mathbf{V}_1.$$

After we restored the state vector, we can use control laws (in which it is suggested that the full state vector is known), replacing true state with the restored one.

Thus the optimal control law is a combination of optimal stochastic observer, in which the systems state is restored. And the optimal deterministic controller, that is immediate linear function of restored state vector. This result is knows as the separation principle [1].

To solve the problems of optimal deterministic controller construction it is necessary to minimizes integral quadratic criteria:

$$J_d = \sum_0^{\infty}(\mathbf{x}^T\mathbf{R}_1\mathbf{x} + \mathbf{u}^T\mathbf{R}_2\mathbf{u}), \quad (1)$$

where $\mathbf{R}_1$, $\mathbf{R}_2$ are non-negatively defined symmetrical matrices.

In criteria (1) first component $\mathbf{x}^T\mathbf{R}_1\mathbf{x}$ is a measure of system's state deviation in moment t from the zero state, and characterizes performance of the control.

Another member of criteria $\mathbf{u}^T\mathbf{R}_2\mathbf{u}$ is calculating the losses of the performance on the control.

Such regulator uses output stationary feedback

$$\mathbf{u}(i) = -\mathbf{F}\hat{\mathbf{x}}(i),\ i = i_0, i_0+1, \ldots, i_1 - 1, \quad (2)$$

where $\mathbf{F}$ is gain coefficients for every variable of state vector.

Meanings of these coefficients for the expression (2) are calculated by the formula:

$$\mathbf{F} = \left(\mathbf{B}_d^{\ T}\mathbf{P}\mathbf{B}_d + \mathbf{R}_1\right)^{-1}\mathbf{B}_d^{\ T}\mathbf{P}\mathbf{A}_d. \quad (3)$$

In the expression (3) $\mathbf{P}$ is a positively defined symmetrical matrix. It is a solution of equation:

$$\mathbf{P} = \mathbf{A}_d^{\ T}\mathbf{P}\mathbf{A}_d - \mathbf{A}_d^T\mathbf{P}\mathbf{B}_d\left(\mathbf{B}_d^T\mathbf{P}\mathbf{B}_d + \mathbf{R}_1\right)\mathbf{B}_d^T\mathbf{P}\mathbf{B}_d + \mathbf{R}_2.$$

Substituting equation (4), (3) for the control law in observer equation (1) can be rewritten in form of:

$$\mathbf{R}_1 - \mathbf{P}\mathbf{B}\mathbf{R}_2^{-1}\mathbf{B}^T\mathbf{P} + \mathbf{A}^T\mathbf{P} + \mathbf{P}\mathbf{A} = 0.$$

Substituting expression (3) for the control law into the observer equation (1), we will obtain the equation of connection of the observers with the controller in the form of

$$\hat{\mathbf{x}}(i+1) = \left[\mathbf{A}_d - \mathbf{B}_d\mathbf{F} - \mathbf{K}\mathbf{C}_d\right]\hat{\mathbf{x}}(i) + \mathbf{K}\mathbf{y}(i).$$

Closed loop system, that is obtained as the result of connection of the plant with the controller is the linear one with dimensions of 2n (where n – is dimension of the state x), that could be described by the system of equations

$$\begin{pmatrix}\mathbf{x}(i+1)\\ \hat{\mathbf{x}}(i+1)\end{pmatrix} = \begin{pmatrix}\mathbf{A}_d & -\mathbf{B}_d\mathbf{F}\\ \mathbf{K}\mathbf{C}_d & \mathbf{A}_d - \mathbf{K}\mathbf{C}_d - \mathbf{B}_d\mathbf{F}\end{pmatrix}\begin{pmatrix}\mathbf{x}(i)\\ \hat{\mathbf{x}}(i)\end{pmatrix}.$$

The next step of design is robust optimization of obtained optimal result [2], [3].

III. DIGITAL CONTROL SYSTEM DESIGN WITH THE REDUCED ORDER OBSERVER

Consider the linear system with the corresponding measurements

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}; \qquad \mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u}.$$

As the number of measurements is less than the number of phase coordinates, it is necessary to define the filter to minimize the error rate $\varepsilon = \mathbf{x} - \hat{\mathbf{x}}$.

Choose a variable $\mathbf{p}(t)$ that is a measure of variables that are not observed $\mathbf{p} = \mathbf{C}'\mathbf{x}$, where $\mathbf{C}'$ is the matrix of variables that must be reconstructed [2], [4]. Then from the relation:

$$\mathbf{y} = \mathbf{C}\mathbf{x}$$
$$\mathbf{p} = \mathbf{C}'\mathbf{x}$$

Assume that exists a matrix $\mathbf{C}_1$ such that

$$rank\begin{bmatrix}\mathbf{C}\\ \mathbf{C}_1\end{bmatrix} = n,$$

where $\mathbf{C}_1$ is matrix of variable, which is necessary to restore. So

$$\mathbf{x}(t) = \begin{bmatrix}\mathbf{C}\\ \mathbf{C}_1\end{bmatrix}^{-1}\begin{bmatrix}\mathbf{y}(t)\\ \mathbf{p}(t)\end{bmatrix}$$

Introduce the notation

$$\begin{bmatrix} \mathbf{C} \\ \mathbf{C}_1 \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{L}_1 & \mathbf{L}_2 \end{bmatrix}$$

so that

$$\mathbf{x}(t) = \mathbf{L}_1\mathbf{y}(t) + \mathbf{L}_2\mathbf{p}(t).$$

An observer for $\mathbf{p}(t)$ can be constructed by finding first a differential equation for $\mathbf{p}(t)$, that is $\dot{\mathbf{p}}(t) = \mathbf{C}_1\dot{x}(t) = = \mathbf{C}_1\mathbf{A}x(t) + \mathbf{C}_1\mathbf{B}u(t) = \mathbf{C}_1\mathbf{A}\mathbf{L}_2 p(t) + \mathbf{C}_1$. To see that, we first observe that

$$\begin{bmatrix} \mathbf{C} \\ \mathbf{C}_1 \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{L}_1 & \mathbf{L}_2 \end{bmatrix} \Rightarrow \begin{bmatrix} \mathbf{C} \\ \mathbf{C}_1 \end{bmatrix}\begin{bmatrix} \mathbf{C} \\ \mathbf{C}_1 \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{C} \\ \mathbf{C}_1 \end{bmatrix}\begin{bmatrix} \mathbf{L}_1 & \mathbf{L}_2 \end{bmatrix} = \mathbf{I}.$$

The measurement are given by

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) = \mathbf{C}\mathbf{L}_1\mathbf{y}(t) + \mathbf{C}\mathbf{L}_2.$$

If we differentiate the output variable we get

$$\dot{\mathbf{y}} = \mathbf{C}\dot{\mathbf{x}} = \mathbf{C}\mathbf{A}\mathbf{x} + \mathbf{C}\mathbf{B}\mathbf{u} = \mathbf{C}\mathbf{A}\mathbf{L}_2\mathbf{p} + \mathbf{C}\mathbf{A}\mathbf{L}_1\mathbf{y} + \mathbf{C}\mathbf{B}\mathbf{u},$$

i. e. $\dot{\mathbf{y}}$ carries information about $\mathbf{p}(t)$. An observer for $\mathbf{p}(t)$ is obtained from the last two equations as

$$\dot{\hat{\mathbf{p}}} = \mathbf{C}_1\mathbf{A}\mathbf{L}_2\hat{\mathbf{p}} + \mathbf{C}_1\mathbf{A}\mathbf{L}_1\mathbf{y} + \mathbf{C}_1\mathbf{B}\mathbf{u} + \mathbf{K}(\dot{\mathbf{y}} - \dot{\hat{\mathbf{y}}}),$$

where $\mathbf{K}$ is the observer gain. If in the differential equation for $\mathbf{y}(t)$ we replace $\mathbf{p}(t)$ by its estimate, we will have

$$\dot{\hat{\mathbf{y}}} = \mathbf{C}\mathbf{A}\mathbf{L}_1\hat{\mathbf{p}} + \mathbf{C}\mathbf{A}\mathbf{L}_1\mathbf{y} + \mathbf{C}\mathbf{B}\mathbf{u}.$$

This produces the following observer for $\mathbf{p}$

$$\begin{aligned} \dot{\hat{\mathbf{p}}} = \mathbf{C}_1\mathbf{A}\mathbf{L}_2\hat{\mathbf{p}} + \mathbf{C}\mathbf{A}\mathbf{L}_1\mathbf{y} + \mathbf{C}_1\mathbf{B}\mathbf{u} \\ + \mathbf{K}(\mathbf{y} - \mathbf{C}\mathbf{A}\mathbf{L}_2\mathbf{p} - \mathbf{C}\mathbf{A}\mathbf{L}_1\mathbf{y} - \mathbf{C}\mathbf{B}\mathbf{u}). \end{aligned} \tag{4}$$

Since it is impractical and undesirable to differentiate $\mathbf{y}(t)$ in order to get $\dot{\mathbf{y}}(t)$ (this operation introduces noise in practice), we take the change of variables

$$\hat{\mathbf{q}} = \mathbf{p} - \mathbf{K}_1\mathbf{y}.$$

This leads to an observer for $\hat{\mathbf{q}}(t)$ of the form

$$\dot{\hat{\mathbf{q}}}(t) = \mathbf{A}_q\hat{\mathbf{q}}(t) + \mathbf{B}_{qu}\mathbf{u}(y) + \mathbf{B}_{qy}\mathbf{y}(t), \tag{5}$$

where

$$\mathbf{A}_q = \mathbf{C}_1\mathbf{A}\mathbf{L}_2 - \mathbf{K}_1\mathbf{C}\mathbf{A}\mathbf{L}_2;$$

$$\mathbf{B}_{qu} = \mathbf{C}_1\mathbf{B} - \mathbf{K}_1\mathbf{C}\mathbf{B};$$

$$\mathbf{B}_{qy} = \mathbf{C}_1\mathbf{A}\mathbf{L}_2\mathbf{K}_1 + \mathbf{C}_1\mathbf{A}\mathbf{L}_1 - \mathbf{K}_1\mathbf{C}\mathbf{A}\mathbf{L}_1 - \mathbf{K}_1\mathbf{C}\mathbf{A}\mathbf{L}_2.$$

The estimates of the original system state space variables are now obtained as

$$\hat{\mathbf{x}}(t) = \mathbf{L}_1\mathbf{y}(t) + \mathbf{L}_2\hat{\mathbf{p}}(t) = \mathbf{L}_2\hat{\mathbf{q}}(t) + (\mathbf{L}_1 + \mathbf{L}_2\mathbf{K}_1)\mathbf{y}(t).$$

The equations (4), (5) describe the reduced order observer.

To convert continuous to discrete observer, assume

$$\dot{\mathbf{x}} \approx \frac{\mathbf{x}_n - \mathbf{x}_{n-1}}{T},$$

where T is a sampling time of system.

Thus, we will get:

$$\mathbf{x}_n = \mathbf{A}_d\mathbf{x}_{n-1} + \mathbf{B}_d\mathbf{u}_n;$$
$$\mathbf{y}_n = \mathbf{C}_d\mathbf{x}_n + \mathbf{D}_d\mathbf{u}_n,$$

where $\mathbf{C}_d = \mathbf{C}$, $\mathbf{D}_d = \mathbf{D}$, $\mathbf{A}_d = \mathbf{E} + T\mathbf{A}$, $\mathbf{B}_d = T\mathbf{B}$, $\mathbf{E}$ are unit matrix.

After we restored the state vector, we can use control laws (in which it is suggested that the full state vector is known), replacing true state with the restored one.

Thus the optimal control law is a combination of reduced order deterministic observer, in which the systems state is restored. And the optimal deterministic controller, that is immediate linear function of restored state vector. This result is knows as the separation principle in implicit form [1], [2], [3]. The procedure of optimal regulator synthesis is same as with Kalman filter.

IV. Robust optimization of obtained optimal result

The robustness requirements to the design of the flight control system include some specifications of parameter uncertainty, within which control system must preserve its stability and acceptable performance. This uncertainty could be caused by various physical reasons, which produce certain deviation of model's parameters from their "nominal" values. In this case we can consider several models, produced by parametric disturbances, and the task of the robust control is to find such single controller, which could guarantee stability and acceptable performance for the family of the nominal and perturbed models. This approach is called multi-model NPRS approach [2], [3].

For the sake of brevity and without loss of generality we consider two plant's models: nominal and perturbed, which are represented by two quadruples of matrices [**A**, **B**, **C**, **D**] and [$\mathbf{A_p}$, $\mathbf{B_p}$, $\mathbf{C_p}$, $\mathbf{D_p}$] respectively [2], [3]. Number of perturbed models could be increased to any appropriate value, if information about all them is available. The problem is to find the same control law for these two models appropriate from the viewpoint of stability and performance. The solution of this problem can be achieved by the convex optimization procedure using composite performance index (CPI), consisting from estimations of performance and robustness for the nominal and perturbed systems with corresponding LaGrange factors, weighting the contribution of each estimation in the CPI [2], [3]:

$$J_{\Sigma} = \lambda_d J_d + \sum_{i=1}^{m} \lambda_{di}^{(p)} J_{di}^{(p)} + \lambda_s J_s + \sum_{i=1}^{m} \lambda_{.si}^{(p)} J_{si}^{(p)}$$
$$+ \lambda_{\infty} \left\| T(j\omega) \right\|_{\infty} + \sum_{i=1}^{m} \lambda_{\infty i}^{(p)} \left\| T_i^{(p)}(j\omega) \right\|_{\infty} + PF,$$

were $\lambda_d, \lambda_s, \lambda_{di}{}^{(p)}, \lambda_{si}{}^{(p)}, \lambda_{\infty}, \lambda_{\infty i}^{(p)}$ are the corresponding weight coefficients [4], [5].

The optimization procedure with different coefficients allows achieving the compromise between robustness and quality.

The last step in the procedure of the robust control system synthesis is a modeling system in Simulink package with all the necessary nonlinear elements belonging to a real system (saturation, dead zone, etc.), and the turbulent wind. Thus, the final conclusion about the control system quality can be done after modeling [2], [3].

V. CASE STUDY AND INVESTIGATE OF INITIAL DATA INFLUENCE

Using the techniques described above flight control systems synthesis was performed for object which described in [2]. Some results of the synthesis are presented in the works [2].

To investigate influence of information on atmospheric turbulence different forming filter was calculated. Forming filter was calculated at root mean square deviations of the wind speed $\delta = 3$ m/s and scales of turbulence $L = 580$, $\delta = 2.5$ m/s and $L = 1000$. The results are listed in Table 1 – 4.

The design of the obtained results for the nominal system in Simulink environment is the final stage of synthesis.

TABLE 1

NOMINAL AND PERTURBED DISCRETE SYSTEMS CHARACTERISTICS (CONTROL LAW WITH KALMAN FILTER) WITH THE DIFFERENT ATMOSPHERE CHARACTERISTICS

Atmosphere characteristics	Plane	Standard deviation					
		V, m/s	α, degree	θ, degree	q, degree /s	h, m	el, degree
δ =2.5m/s L =580	n.	0.0254	0.0374	0.0672	0.1172	0.1975	0.0322
	p.	0.0293	0.0333	0.2841	0.0905	0.1734	0.0278
δ =3m/s L =580	n.	0.0304	0.0482	0.0853	0.1480	0.2363	0.0415
	p.	0.0350	0.0426	0.3051	0.1143	0.2069	0.0356
δ =2.5m/s L =1000	n.*	0.0248	0.0391	0.0675	0.1240	0.2029	0.0320
	p.*	0.0303	0.0358	0.3033	0.1037	0.1835	0.0277

* is on scales of turbulence L =1000 system with a 4 order controller loses stability, order the regulator in this case was reduced only to 7. The table shows the result for a system with 7 order of the regulator.

TABLE 2

H_2-NORM IN THE STOCHASTIC CASE, PHASE AND AMPLITUDE STABILITY FACTOR FOR THE NOMINAL AND PERTURBED SYSTEMS (CONTROL LAW WITH KALMAN FILTER) WITH THE DIFFERENT ATMOSPHERIC CHARACTERISTICS

Characteristics	Plane	δ =2.5m/s, L =580	δ =3m/s L =580	δ =2.5m/s, L =1000
H_2^s	nominal*	0.0396	0.0568	0.0418
	perturbed*	0.0309	0.0440	0.0346
Amplitude stability factor (dB)	nominal*	11.5	10.7	12.9
	perturbed*	13.6	12.9	15.4
Phase stability factor (degree)	nominal*	53.2	51.1	31.1
	perturbed*	58.8	57.6	32.3

TABLE 3

NOMINAL AND PERTURBED DISCRETE SYSTEMS CHARACTERISTICS (CONTROL LAW WITH LUENBERGER OBSERVER) WITH THE DIFFERENT ATMOSPHERE CHARACTERISTICS

Atmosphere characteristics	Plane	Standard deviation					
		V, m/s	α, degree	θ, degree	q, degree /s	h, m	el, degree
δ = 2.5m/s L = 580	n.	0.1251	0.1289	0.2710	0.3963	0.9124	0.1168
	p.	0.2174	0.1556	0.4051	0.4049	1.2380	0.1370
δ = 3m/s L = 580	n.	0.1483	0.1543	0.3237	0.4748	1.0617	0.1399
	p.	0.2622	0.1868	0.4860	0.4856	1.5057	0.1645
δ = 2.5m/s L = 1000	n.	0.1086	0.0988	0.2156	0.3030	0.8521	0.0896
	p.	0.1837	0.1203	0.3209	0.3101	1.1132	0.1059

TABLE 4

H_2-NORM IN THE STOCHASTIC CASE, PHASE AND AMPLITUDE STABILITY FACTOR FOR THE NOMINAL AND PERTURBED SYSTEMS (CONTROL LAW WITH KALMAN FILTER) WITH THE DIFFERENT ATMOSPHERIC CHARACTERISTICS

Characteristics	Plane	δ = 2.5m/s, L = 580	δ = 3m/s, L = 580	δ = 2,5m/s, L = 1000
H_2^s	nominal	0.8482	1.1493	0.7380
	perturbed	1.5799	2.3360	1.2557
Amplitude stability factor (dB)	nominal	13.2	13.2	13.2
	perturbed	17	17	17
Phase stability factor (degree)	nominal	53.1	53.1	53.1
	perturbed	57.1	57.1	57.1

CONCLUSION

Scales of turbulence changing (experimental determination of which is more difficult) has greatly affected on the quality of system with the Kalman filter. The system with third order control law lost stability with increasing the scales of turbulence. Only the seventh order control law provides require stability. This control law is more complicated. So its implementation on a simple onboard computer is not possible in practice.

The change of scale turbulence has a low influence on the quality if the control law with Luenberger observer is used.

REFERENCES

[1] Kwakrenaak, H. and Sivan R. Linear Optimal Control Systems, Wiley-Interscience: New York, 1972.

[2] Tunik A. and Galaguz T. “Robust stabilization and nominal performance of the flight control system for small UAV.” *Applied and computation mathematics*, vol. 3, no. 1, pp. 34–45, 2004.

[3] Kwakernaak H. “Robust Control and H_∞ Optimization.” *Automatika*, vol. 29, no. 2, pp. 255–273, 1993.

[4] Larin, V. B. “Stabilizing control system with static output feedback.” *Journal of Automation and Information Sciences*, no. 2, pp. 19–31, 2004.

[5] Tunik, A.A.; Komnatska, M.M., Klipa A.M. “Static output feedback controller design for flight control system combined with fuzzy control under LMI approach.” *Proceedings 1-st International Conference Methods and Systems of Navigation and Motion Control*. pp. 10–14, October, 13-16, 2010. MIL-STD-1797A 1990, p. 678.

Received 12 August 2014.

Galaguz Tetyana. Ph. D. Associate Professor.
Aircraft Control Systems Department, National Aviation University, Kyiv, Ukraine.
Education: National Airspace University, Kharkiv, Ukraine (2002).
Research area: Control systems.
Publications: 20 papers.
E-mail: T.A.Galaguz@yandex.ua

Т. А. Галагуз. Дослідження впливу початкових даних на якість керування

Досліджено вплив початкових даних на якість керування. Зокрема досліджено зміну якості керування за різних характеристик атмосфери. Синтезовано два закони керування: з використанням фільтра Калмана та з використанням спостерігача Люенбергера. Виконано робастну оптимізацію синтезованих оптимальних законів керування.

Ключові слова: безпілотний літальний апарат; система керування; фільтр Калмана; спостерігач Люенбергера; оптимальний регулятор; фільтр Драйдена.

Галагуз Тетяна Анатоліївна. Кандидат технічних наук. Доцент.
Кафедра систем управління літальних апаратів, Національний авіаційний університет, Київ, Україна.
Освіта: Національний аерокосмічний університет («ХАІ»), Харків, Україна (2002).
Область наукової діяльності: системи управління.
Кількість публікацій: 20.
E-mail: T.A.Galaguz@yandex.ua

Т. А. Галагуз. Исследование влияния начальных данных на качество управления

Исследовано влияние начальных данных на качество управления. Изучено изменение качества управления при разных характеристиках атмосферы. Синтезировано два закона управления: с использованием фильтра Калмана, с использованием наблюдателя Люенбергера. Выполнена робастная оптимизация синтезированных оптимальных законов управления.

Ключевые слова: беспилотный летательный аппарат; система управления; фильтр Калмана; наблюдатель Люенбергера; оптимальный регулятор; фильтр Драйдена.

Галагуз Татьяна. Кандидат технических наук. Доцент.
Кафедра систем управления летательных аппаратов, Национальный авиационный университет, Киев, Украина.
Образование: Национальный аэрокосмический университет («ХАИ»), Харьков, Украина (2002).
Область научной деятельности: системы управления.
Публикаций: 20.
E-mail: T.A.Galaguz@yandex.ua